


LEVEL UP 2023

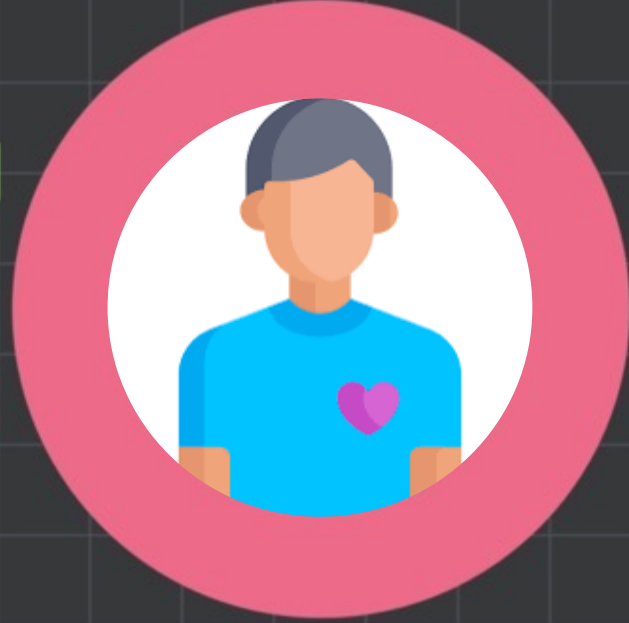
**Our Understanding of the Patient Journey
Through the Health System**

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Actuarial Consultant



Leveling Up Our
understanding of
the patient journey
through the health
system



Our Role In Patient Care

Using Data



Using Data

High-level insights

Granular and intractable

Risk adjustment



IT'S TIME TO UP YOUR GAME △ ○ × □

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High-level insights

Granular and intractable

Risk adjustment



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Using Data

High-level insights

Granular and intractable

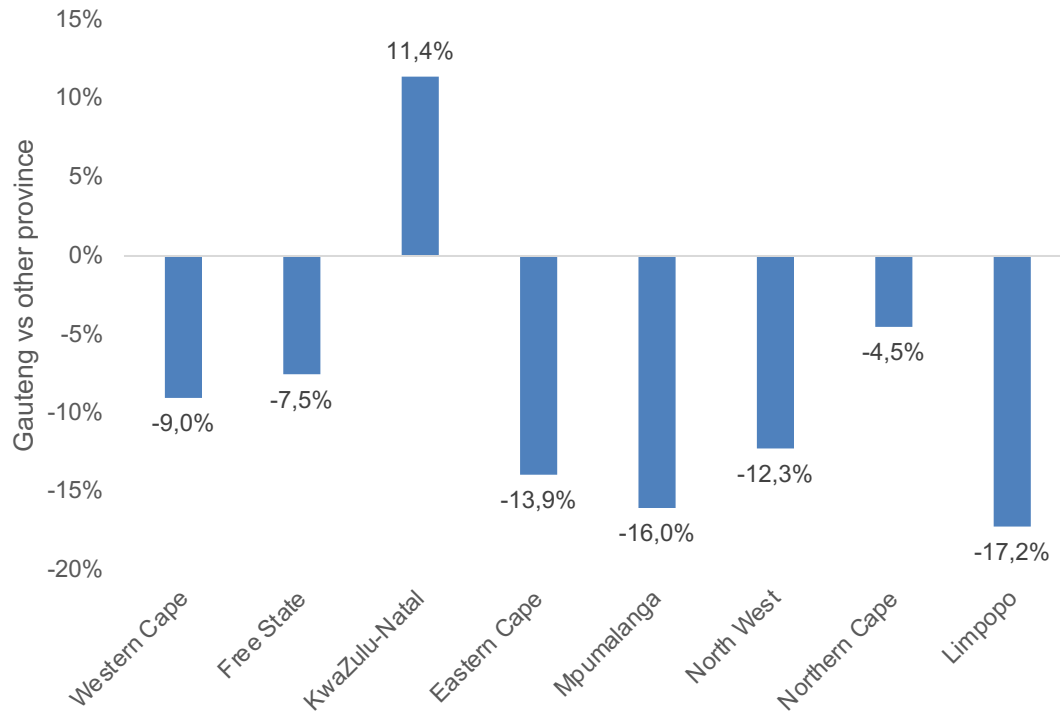
Risk adjustment



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Using Data

There are variations beyond just risk profile that have to be adjusted for.

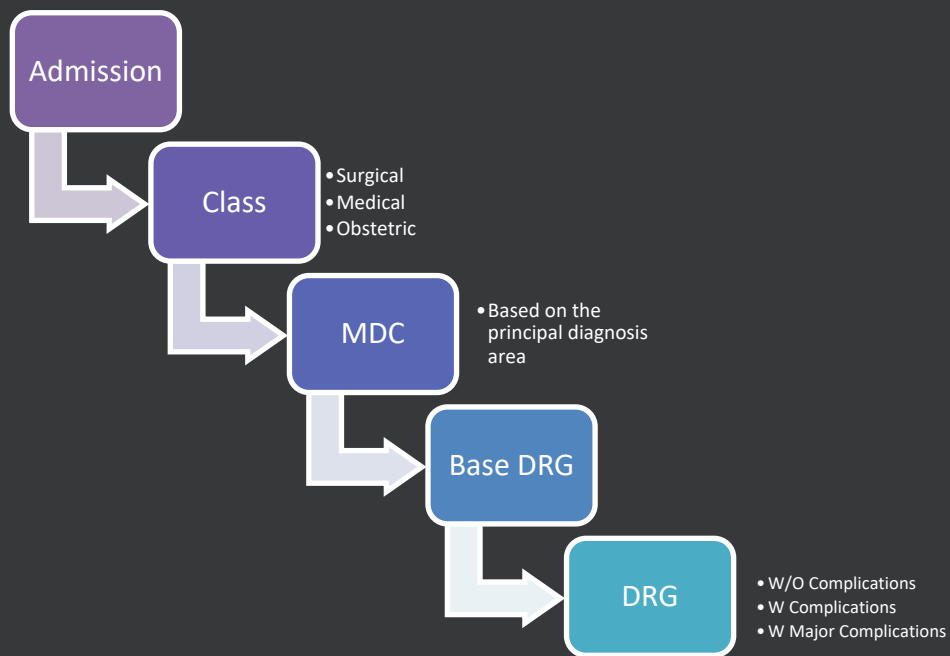


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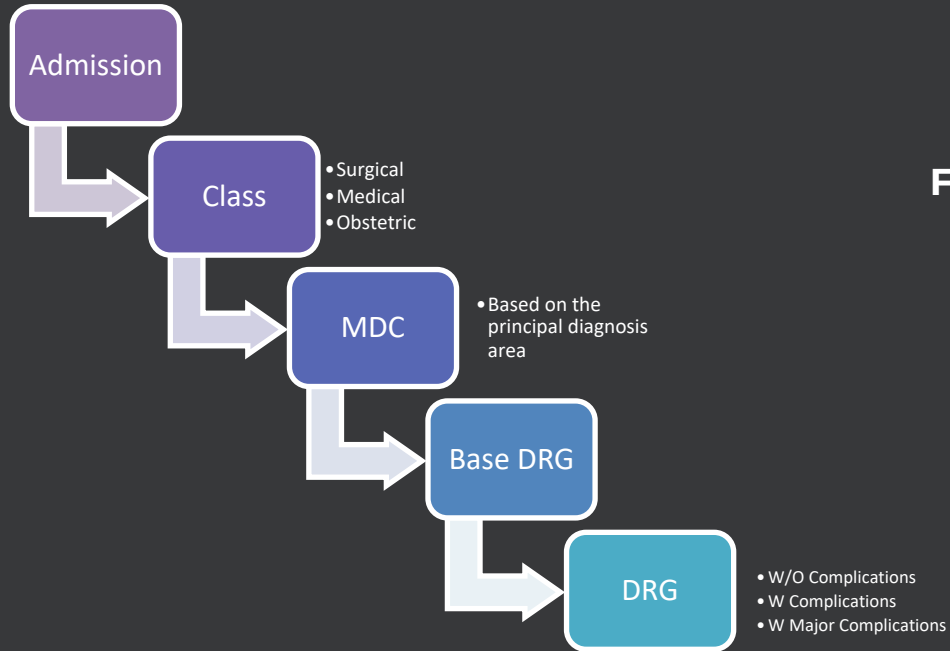


Our Tools

Diagnosis Related Grouper

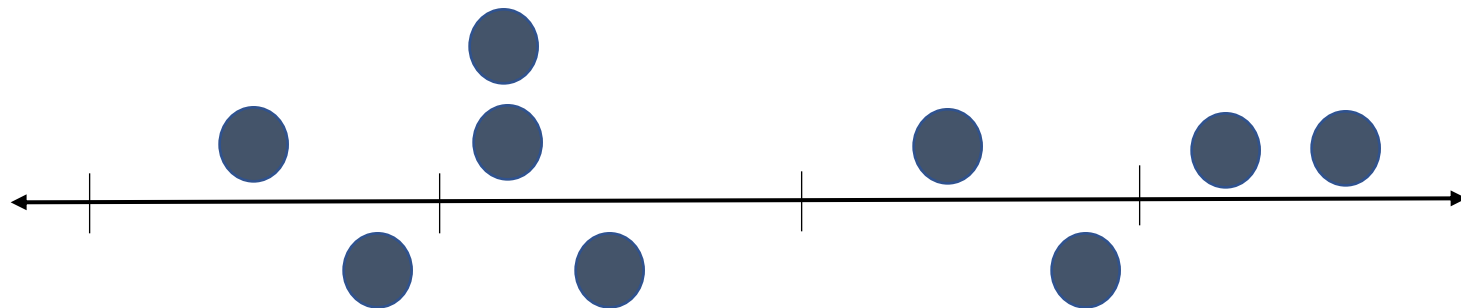


Diagnosis Related Grouper



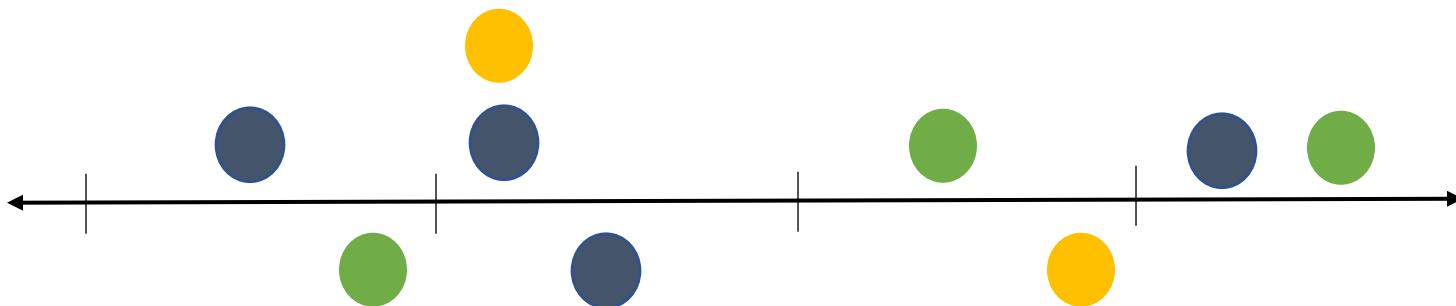
**Focus is on in-hospital
setting**

The Episode Grouper



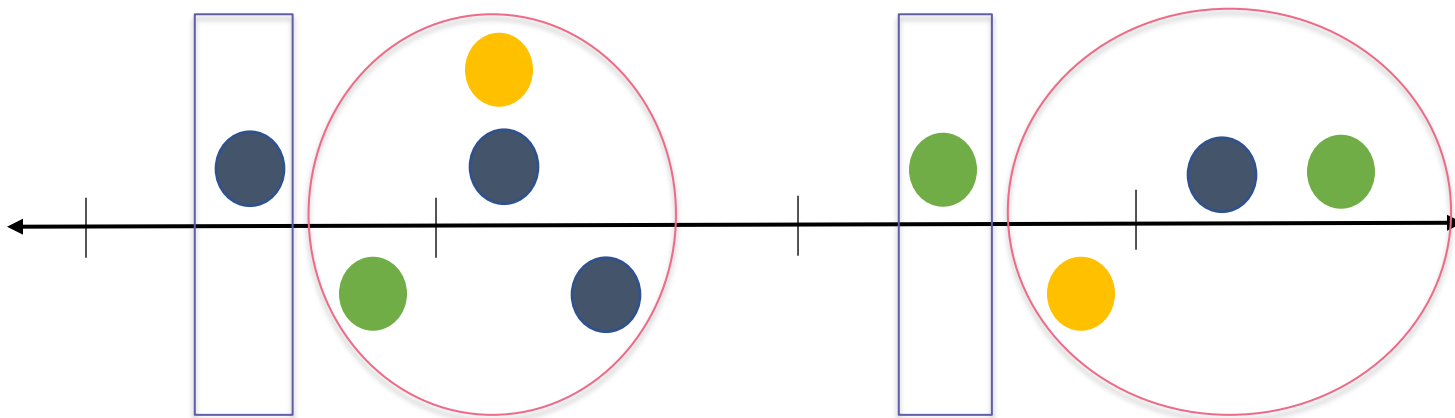
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The Episode Grouper



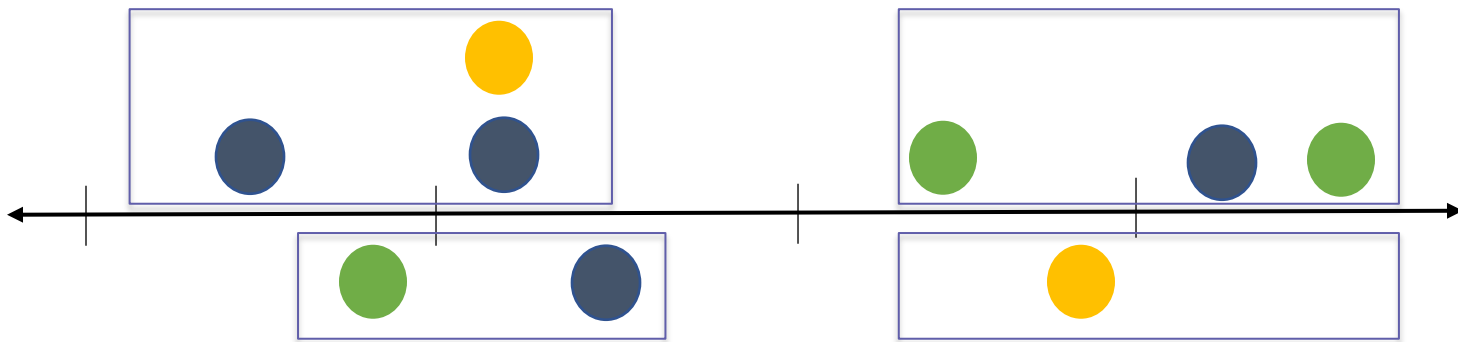
IT'S TIME TO UP YOUR GAME    

The Episode Grouper



IT'S TIME TO UP YOUR GAME △ ○ × □

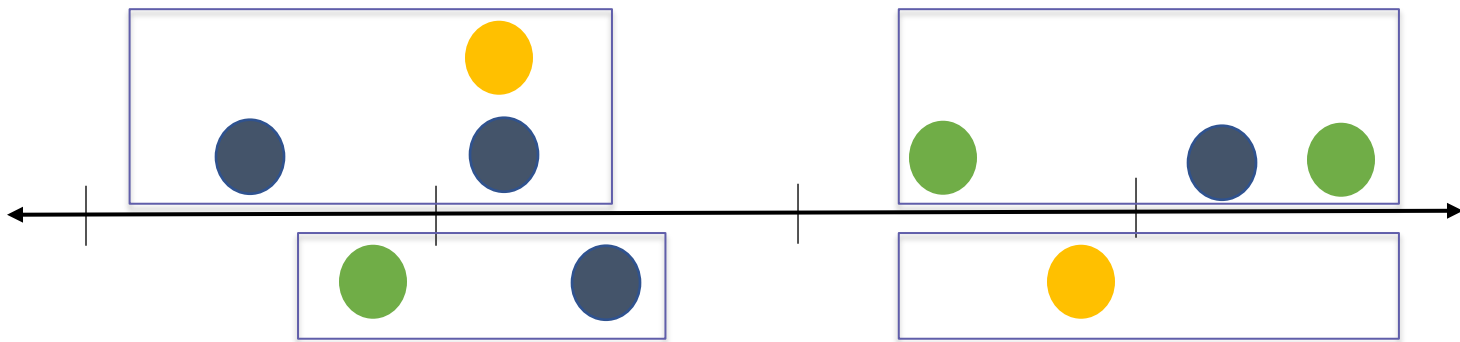
The Episode Grouper



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The Episode Grouper

Can categorize episodes at different levels of granularity



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...so what?

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Applications of the EPG

Risk Management

Identify main contributors to variations in care

Chronic disease management

Structuring ARMs

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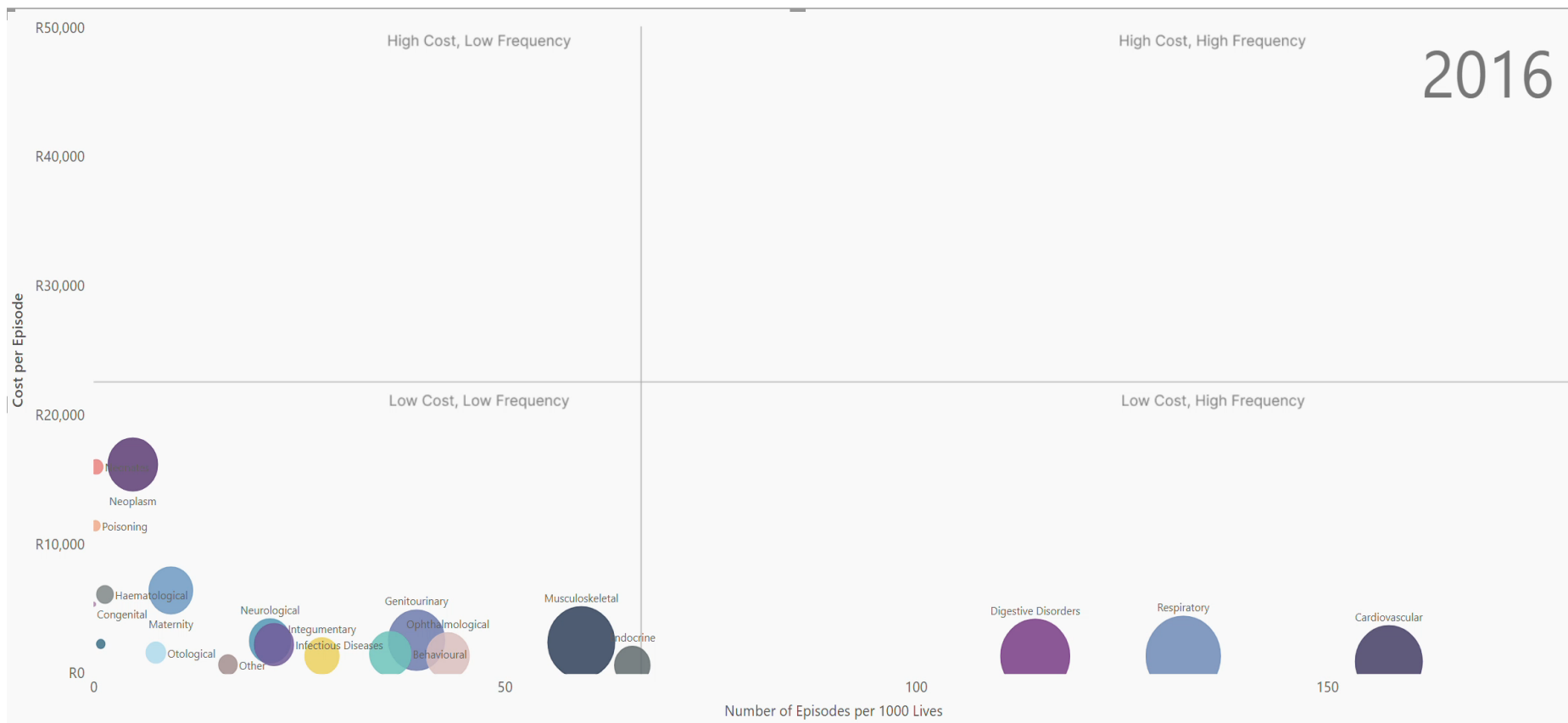
Risk Management

Identify main contributors to variations in care

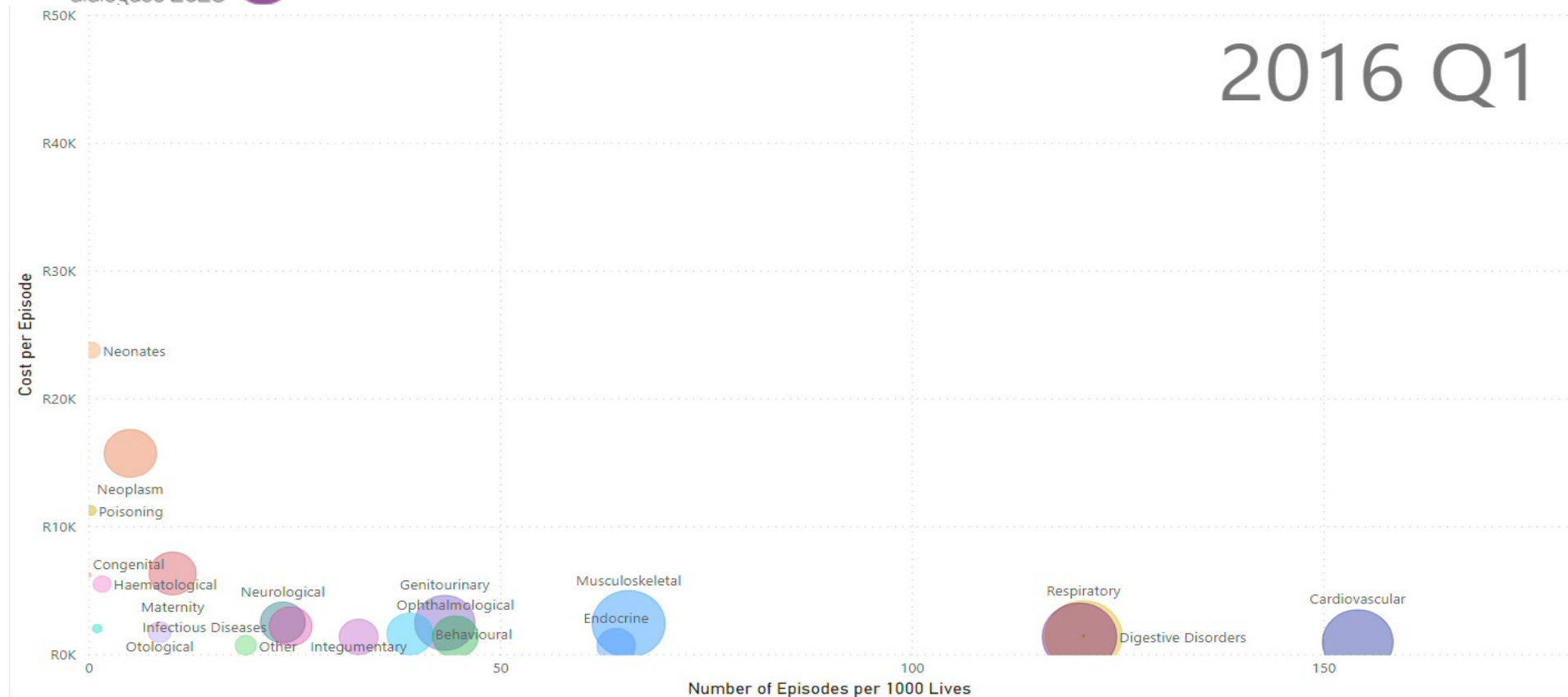
Chronic disease management

Structuring ARMs

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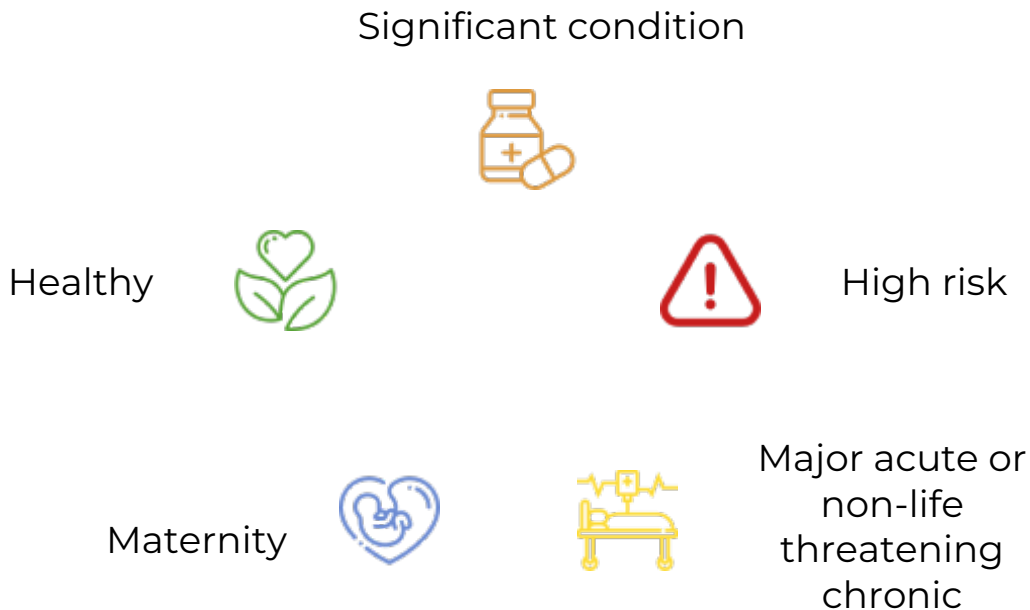
2016 Q1



Risk segmentation

Can look at recent episode history to better categorize current health status

The categories can become more granular



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So we can analyze past trends...



... but what about the future?

So we can analyze past trends...

We can use the EPG to build more detailed risk profiles of lives at a specific point in time.

It is expected that a patient's episode history is a strong contributor to expected future experience.



... but what about the future?

So we can analyze past trends...

We can use the EPG to build more detailed risk profiles of lives at a specific point in time.

It is expected that a patient's episode history is a strong contributor to expected future experience.

So let us use it.



... but what about the future?

GLM Model

Given a member's risk profile and episode history, what is their probability of any admission in the next year?

A GLM is easy to apply but there are many specifications to consider with numerous combinations of interactions between variables.

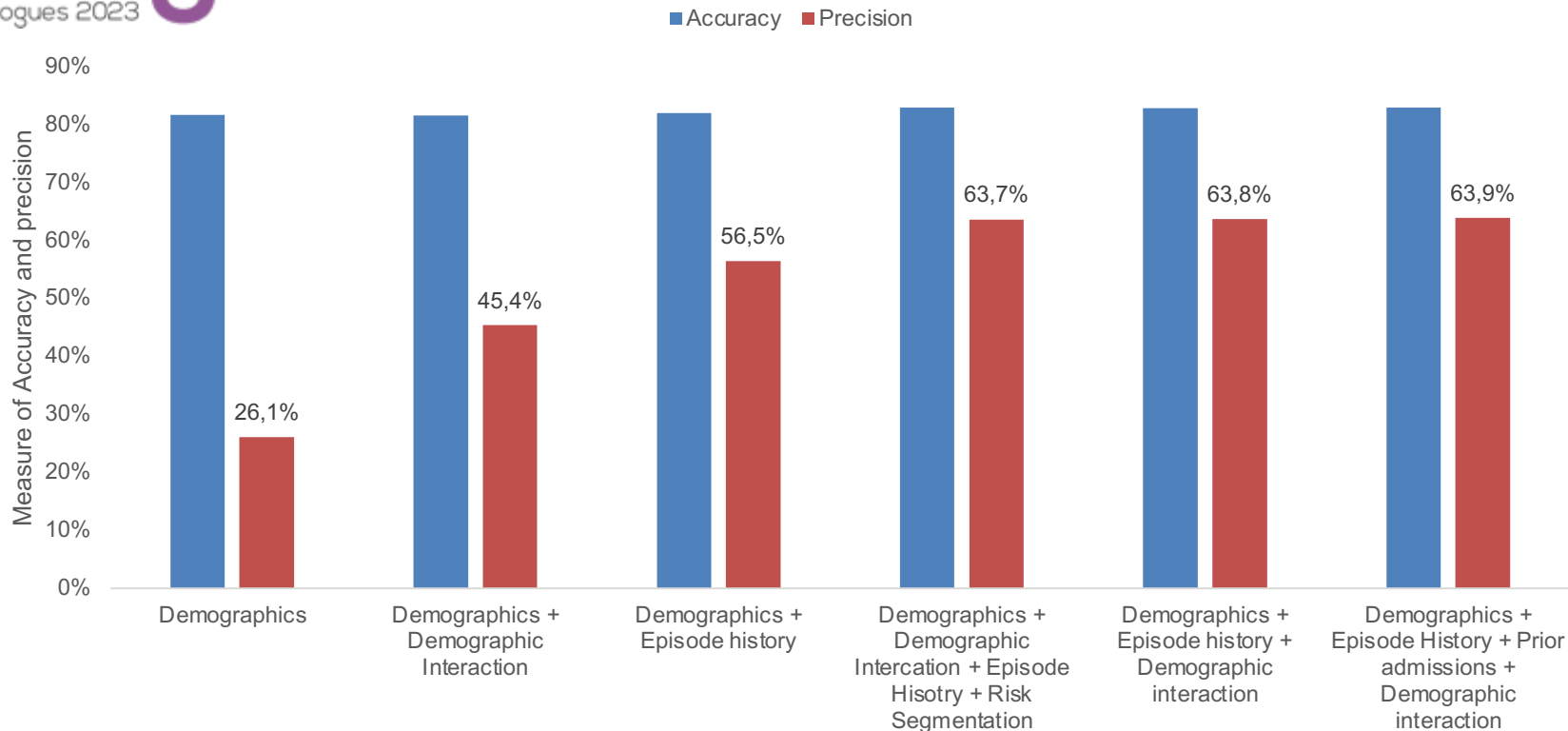
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GLM Model

Accuracy → of all predicted values what % is correct

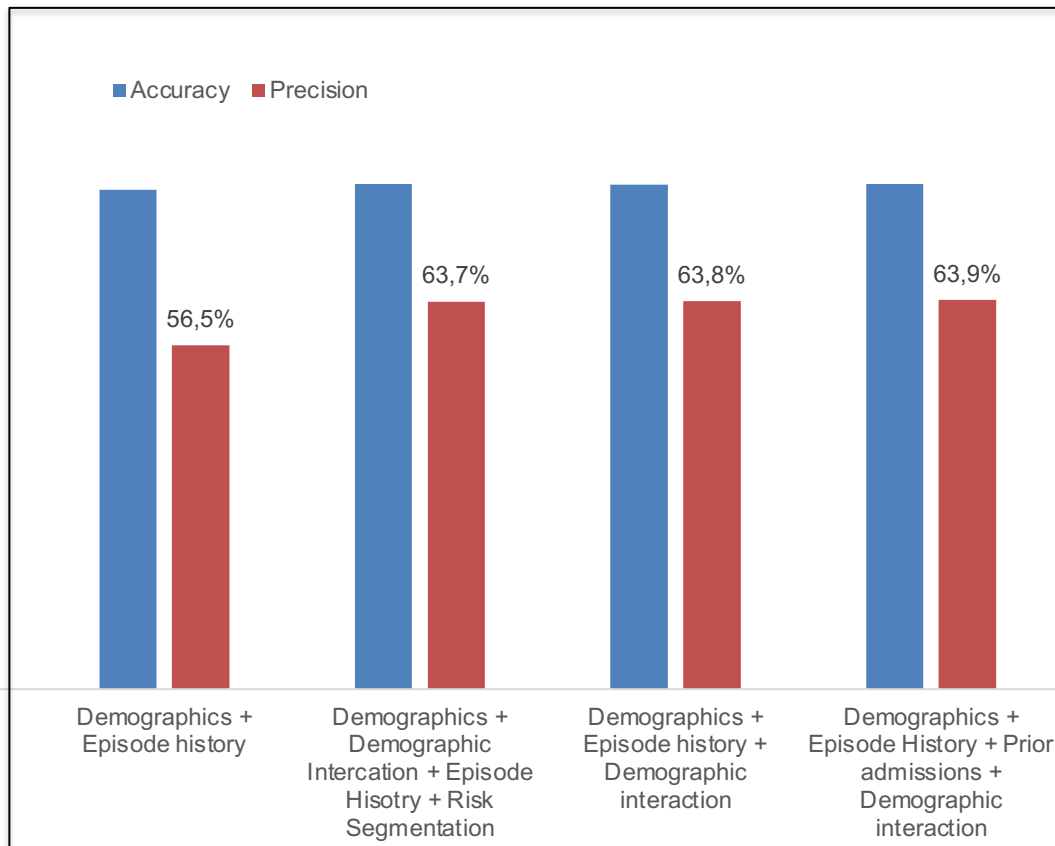
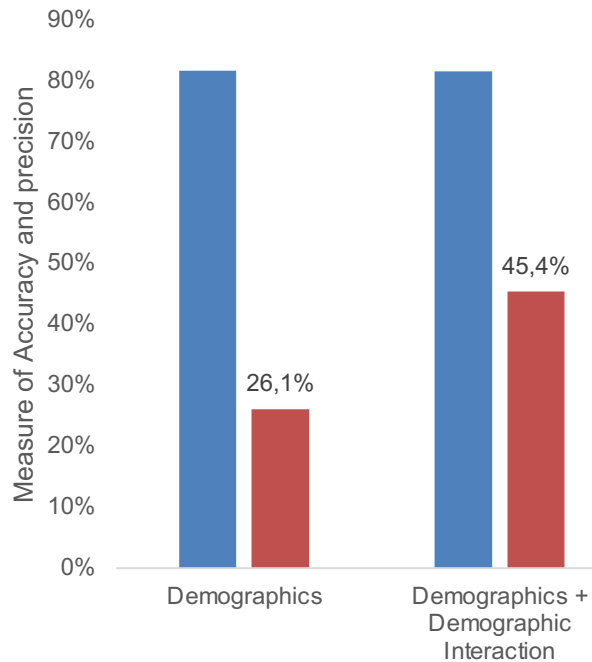
Precision → of all positive predicted values what % is correct

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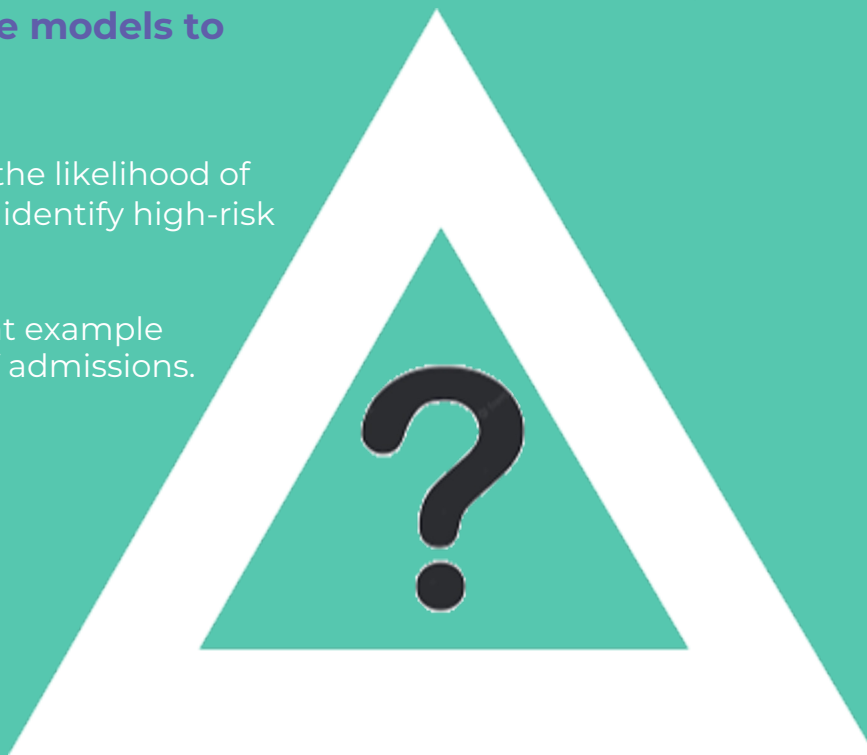
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How can we tailor these models to guide interventions?

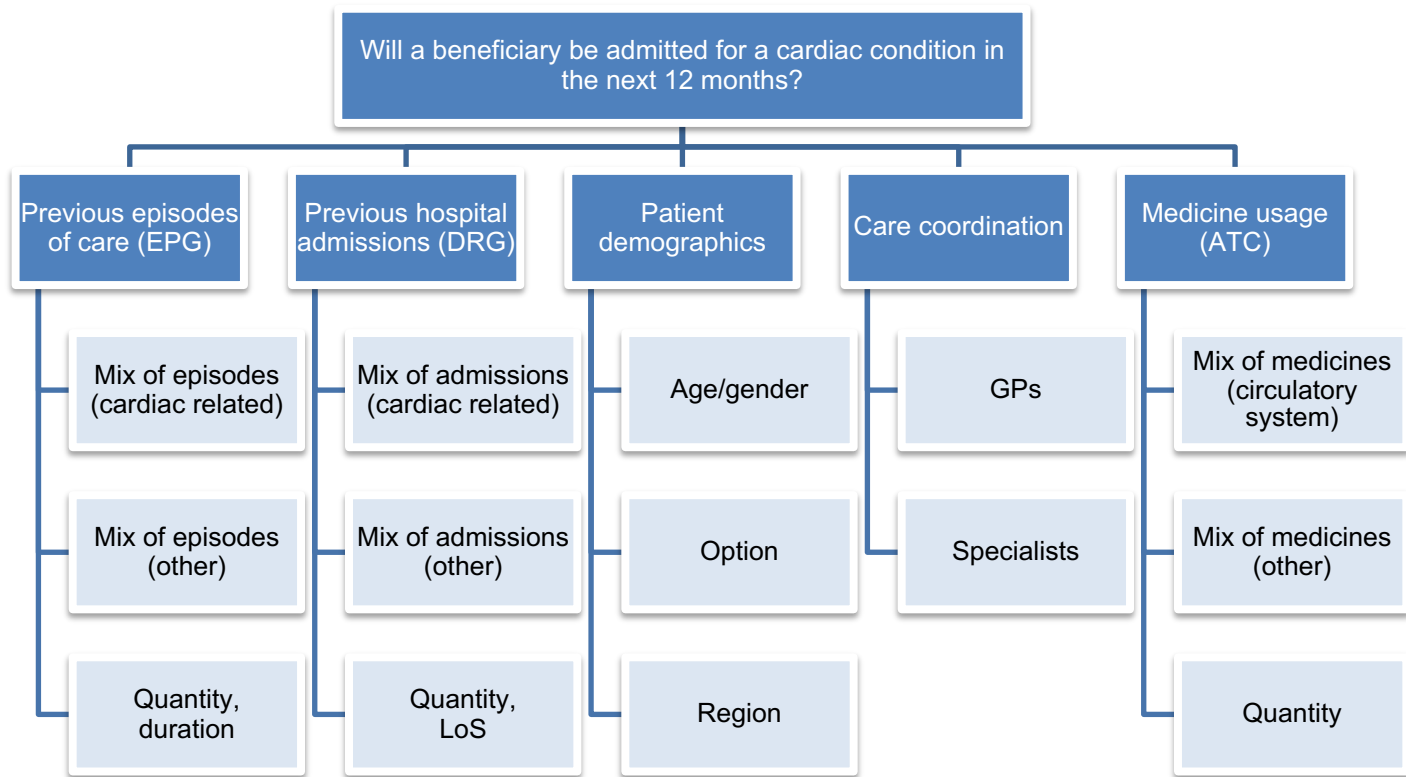
This approach to modelling the likelihood of admission can be applied to identify high-risk beneficiaries.

We could consider a different example focussing on a specific set of admissions.



Cardiac admissions

Model can draw from various sources informing patient journeys

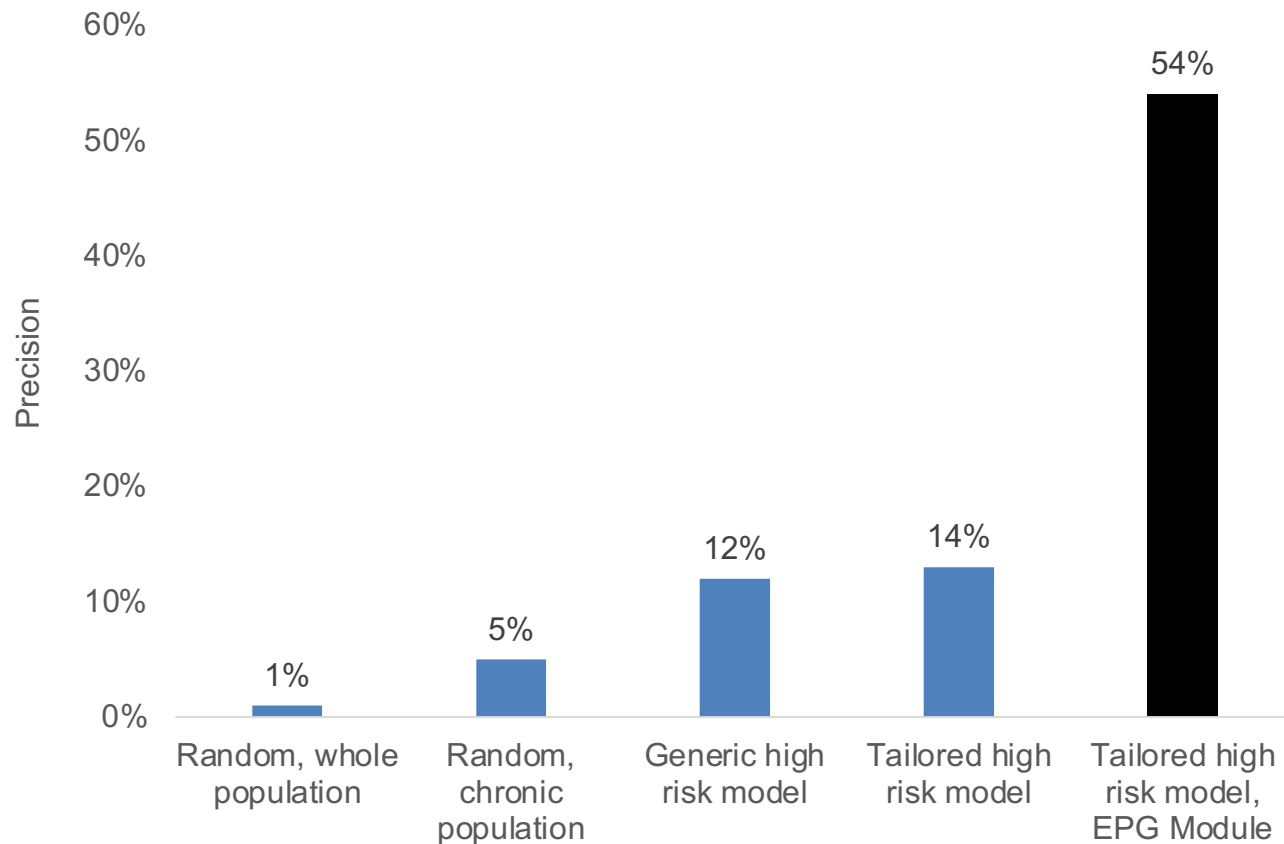


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Cardiac admissions

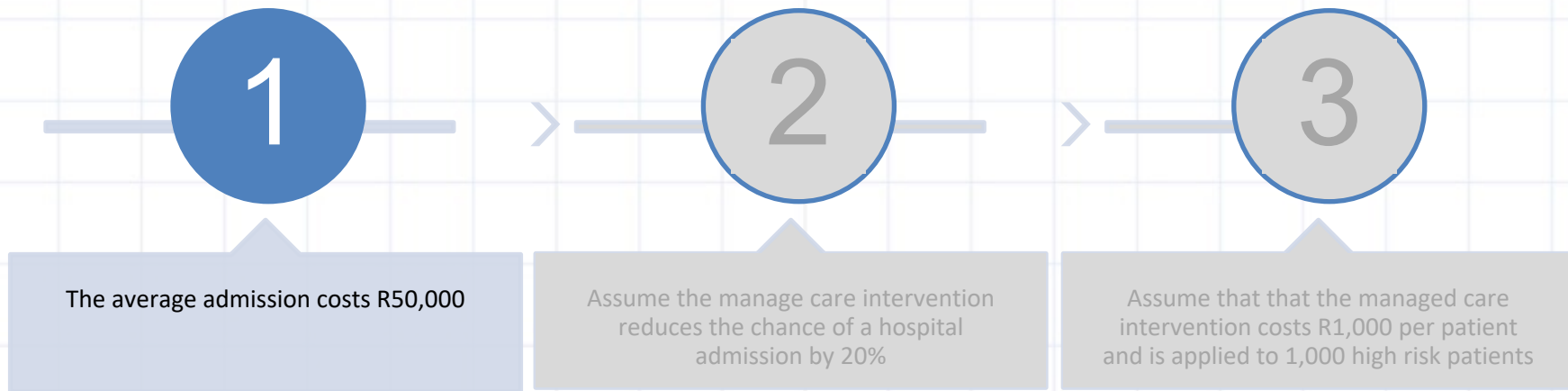
Precision is of greater concern for assessing interventions



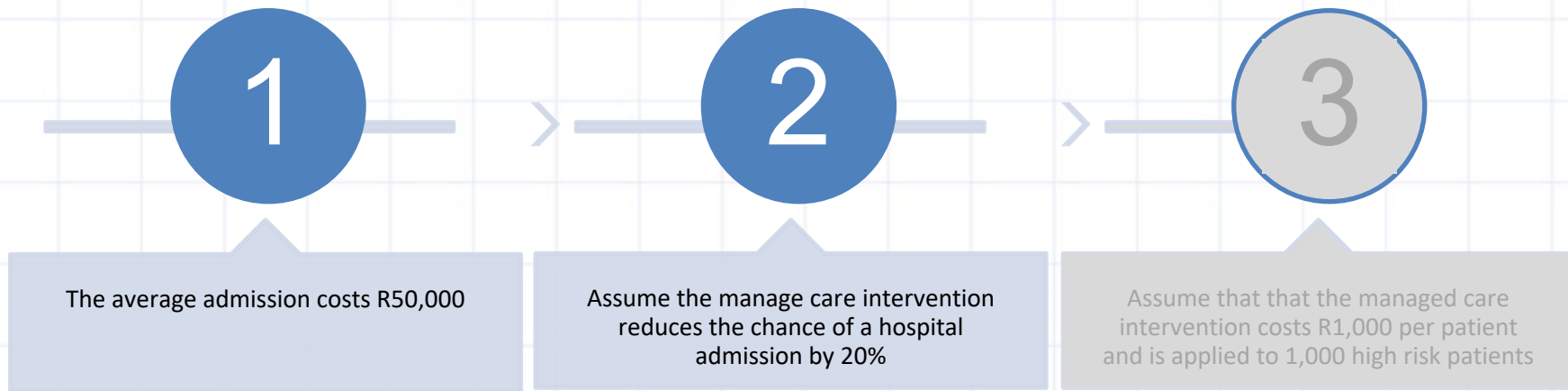
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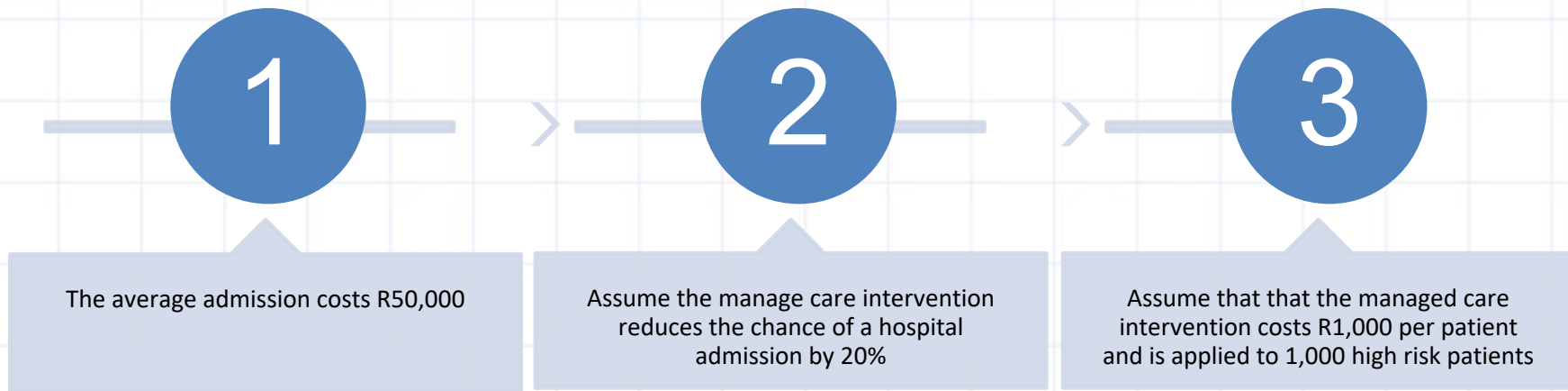
Assessing interventions| Weak modelling (14% precision)



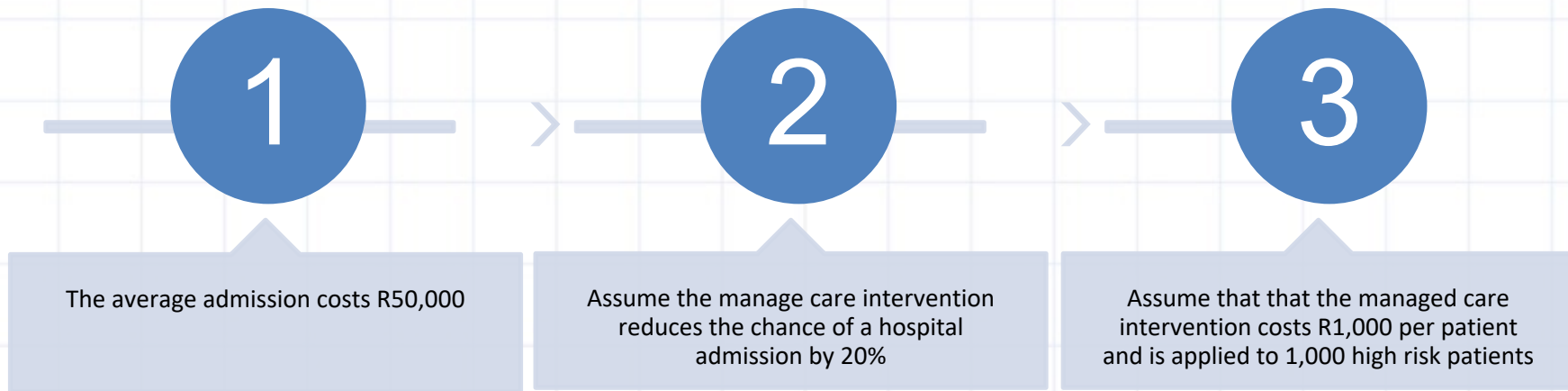
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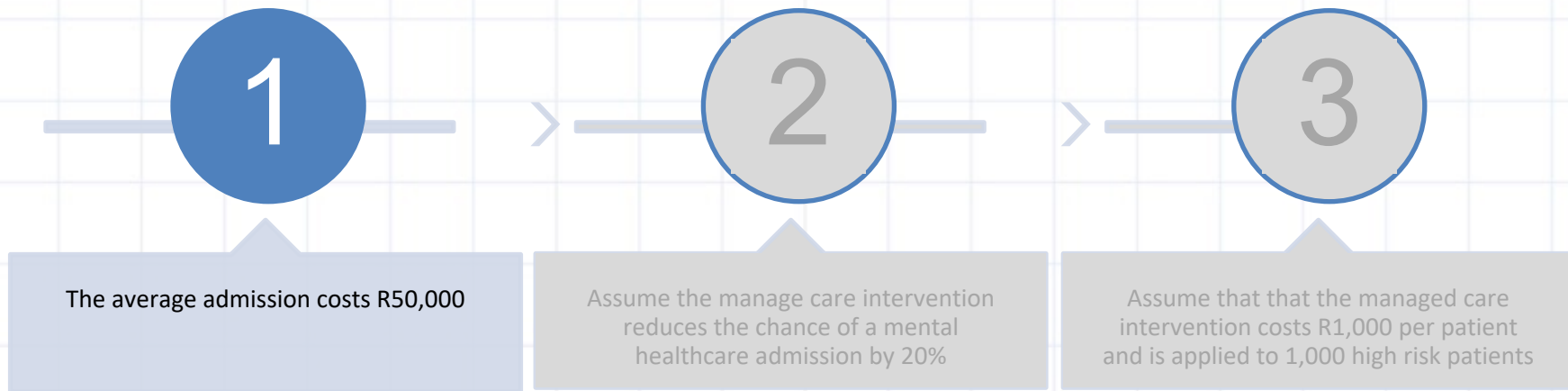
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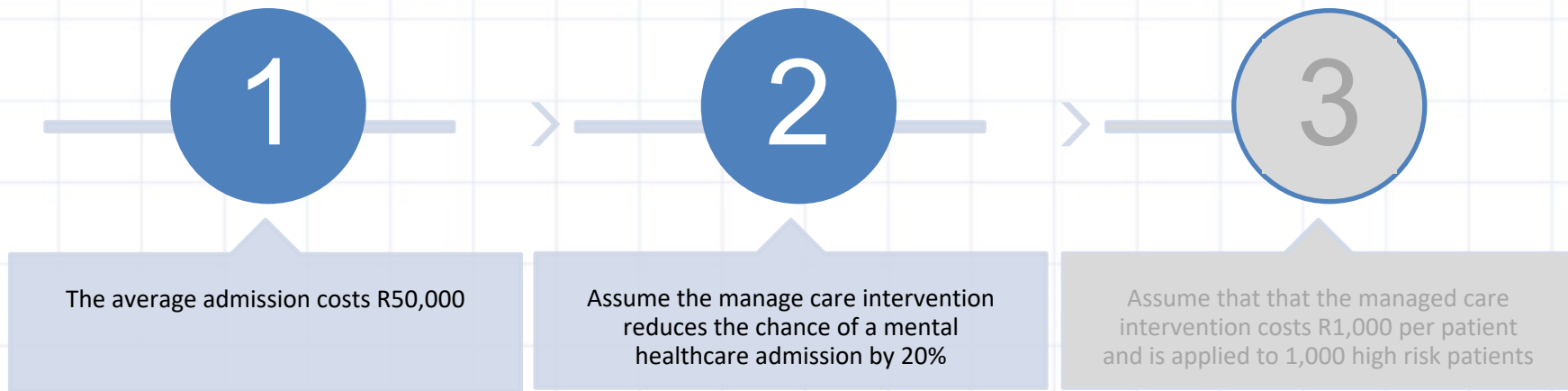
The 1,000 high-risk beneficiaries identified will be responsible for 140 admissions in the absence of managed care interventions. A 20% reduction in the admission rate means that 28 admission will be avoided and R1,400,000 will be saved. The intervention will cost R1,000,000.

The net effect is **savings of just R400,000** and **only 28 beneficiaries will benefit**.

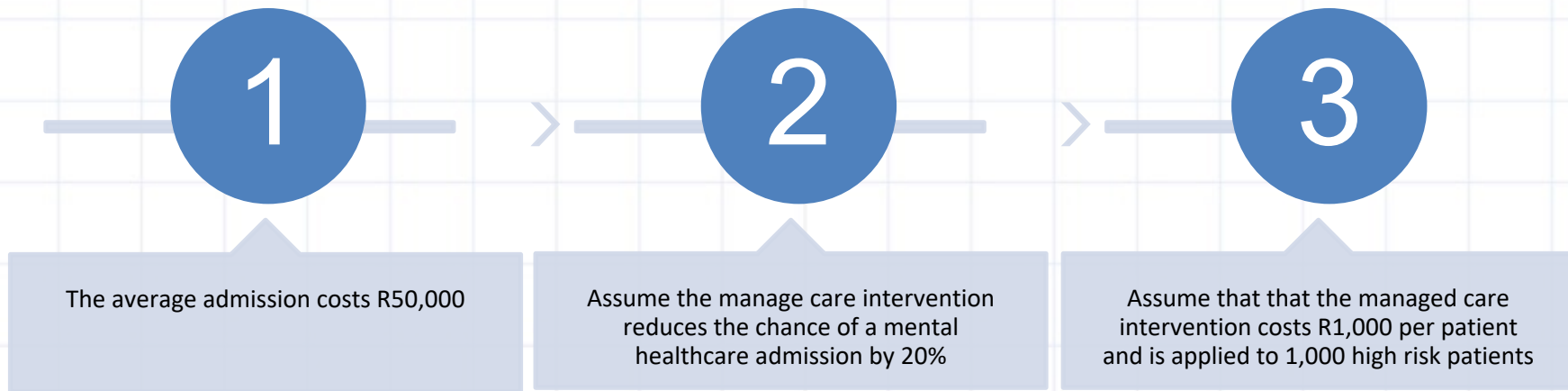
Assessing interventions| Stronger modelling (54% Precision)



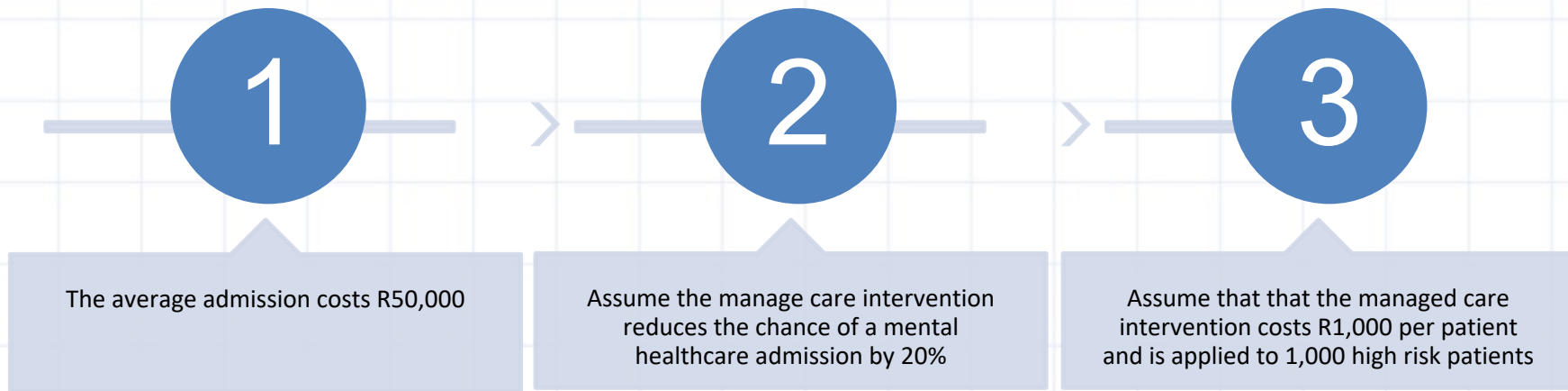
Assessing interventions| Stronger modelling (54% Precision)



Assessing interventions| Stronger modelling (54% Precision)



Assessing interventions| Stronger modelling (54% Precision)



The 1,000 high-risk beneficiaries identified will be responsible for 540 admissions in the absence of managed care interventions. A 20% reduction in the admission rate means that 108 admissions will be avoided and R5,400,000 will be saved. The intervention will cost R1,000,000.

The net effect is a **savings of R4,400,000** and **108 beneficiaries** will benefit.

A way forward

The image features a dark gray background with a repeating pattern of light gray geometric shapes: circles, squares, and triangles. Some of these shapes contain an 'X'. Overlaid on this background is a large, thick pink circle. Inside the pink circle, the words "Thank You." are written in a white, bold, sans-serif font, centered horizontally and vertically.

**Thank
You.**